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AN EMPIRICAL INDEX FOR LABOR MARKET DENSITY

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Abstract——We derive a structural index for labor market density based on the Ellison-Glaeser index for industry concentration. The labor market density index serves as a proxy for the number of workers that are potentially available for jobs in a particular area. The index is based on observed home-work location patterns. It is particularly useful for testing theories where the scale of the market matters. We apply this index to a standard wage equation and find that it explains almost half of the cross-region wage variance.

I. Introduction

SEARCH frictions play an important role in the labor market. Job seekers and vacancies do not meet instantaneously; their matching takes effort and time. The efficiency of this matching process depends on the characteristics of the labor market. An obvious factor that matters is the density of the market: the more job seekers and vacancies are available in a particular area, the easier it is for them to find an acceptable match. Several authors have developed empirical models along these lines; see for example Diamond (1982), Burda and Profit (1996), Coles and Smith (1998), Wasmer and Zenou (1999), Wheeler (2002), and Glaeser and Maré (2001). Although there is a large literature that suggests that returns to scale in job search are constant, there is a good reason why the numbers of job seekers and vacancies might matter: A larger labor market allows workers and firms to be more choosy, so it reduces mismatch. This effect is typically ignored in the empirical matching literature, which is based on aggregated time series data.

A big obstacle in research in this area is that labor market density is difficult to measure. One likely candidate for a measure is simply the number of workers and/or jobs per square mile. However, a number of serious drawbacks to this measure immediately come to mind. First, it ignores the role of infrastructure. What we are really interested in is not the set of applicants within a certain distance of the job, but the number of workers that are potentially available for a job in a certain region. The relevant labor market area should then be weighted by the number of highways and public transport facilities. Moreover, when particular regions are more attractive as residential areas, people might be prepared to accept on average a longer commuting time.

These considerations suggest that we should look for an index based on revealed preferences. The index that we propose is based on observed home-work location patterns. The idea is that we take the location of the job of a worker as given and then analyze where that worker lives. To clarify this idea, assume for the sake of argument that the economy consists of a number of areas with an equal number of inhabitants, say n. Then, if we observe that all workers live in the same area as where they work, a given job can only be occupied by n workers. This is typical for a small-scale labor market. Alternatively, if workers working in a particular location live in 10 different areas, then $10n$ workers can potentially take jobs in that area and the scale of the labor market is large. More specifically, our index can be viewed as a model-based index of geographic labor market density similar to the dartboard index for industry concentration due to Ellison and Glaeser (1997; henceforth EG). The index can take any value between 0 and 1. When it is equal to 1, the only workers who work in a particular area are the ones who live there. When it is equal to 0, the labor market is extremely dense and we observe workers from many different areas to be employed in it. In other words, when many workers are available for a particular job in a particular area, we call that area dense.

The plan of the paper is as follows. Section II derives the index from location decisions of utility-maximizing agents. Section III describes how the index can be constructed from the 5% PUMS of the Census and how it can be linked to the (C)MSA areas of the CPS. Finally, section IV gives an illustration of how the index can be applied in a wage equation and in a model for the cost-of-living index. We find that 45% of the regional variation is captured by our density index.

II. The Index

This section presents the density index, which is a special case of EG's index for industry concentration. Consider the decision problem for the k^{th} worker with a job in area w who has to choose an area h_k to live in. We take the distribution of jobs across areas as given and define f_w as the fraction of jobs located in area w. Let the utility for area h be given by

$$\log \pi_{kwh} = \log \bar{\pi}_{wh} + \varepsilon_{kwh}, \tag{1}$$

where the ε_{kwh}'s reflect idiosyncratic factors (like the relative preference for clean air, safety, theater availability, and so on), which are assumed to be independent Weibull random variables which are also independent of $\{\bar{\pi}_{wh}\}$, and $\bar{\pi}_{wh}$ is a random location-specific variable, which is chosen by nature at the start of the process. It reflects the attractiveness of living in a certain area (given that the agent's job

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is in w) for a typical agent. Conditional on the realization of the random variables $\bar{\pi}_{w1}, \ldots, \bar{\pi}_{wH}$, and given our assumptions on ε_{kwh}, we can write the probability that an agent chooses area h as

$$\mathrm{Prob}\{h_k = h | \bar{\pi}_{w1}, \ldots, \bar{\pi}_{wH}\} = \frac{\bar{\pi}_{wh}}{\sum_j \bar{\pi}_{wj}} \equiv p_{wh},$$

which is a conditional logit model (see McFadden, 1973). Note that p_{wh} is a random variable because $\bar{\pi}_{wj}$ are random variables. We assume that the distribution of p_{wh} is such that

$$\sum_w f_w p_{wh} = \mu_h, \tag{2}$$

$$\mathrm{var}(p_{wh}) = \gamma_w \mu_h (1 - \mu_h), \tag{3}$$

where $\mu_h \in [0, 1]$ and $\gamma_w \in [0, 1]$. Equation (2) implies $E(p_{wh}) = \mu_h$, where the expectation is taken over individuals k. Let x_h be the fraction of the total population that chooses to live in area h. Then[1]

$$E(x_h) = \sum_w f_w p_{wh} = \mu_h.$$

The parameter μ_h drives the overall distribution of workers' home location across areas h. Hence, $\sum_h \mu_h = 1$. An appropriate choice of μ_h reproduces the distribution of home locations that is actually observed in the data, that is, it puts more workers in New York than in Kansas. The variance of p_{wh} measures how sensitive the agent's utility is to region-specific factors. For jobs in nondense areas the variance is likely to be high, because, given the location of the job, there are few areas that have a sufficiently high value of $\bar{\pi}_{wh}$, while the rest of the areas have $\bar{\pi}_{wh} = 0$. When $\gamma_w = 1$, the variance of p_{wh} reaches a maximum (since the maximum of the variance of a random variable with support between 0 and 1 with mean $\mu_h \in [0, 1]$ is $\mu_h[1 - \mu_h]$). In that case, the variation in idiosyncratic characteristics ε_{kwh} is dominated by the variation in the location-specific factors, $\log \bar{\pi}_{wh}$. When $\gamma_w = 0$, the location decision is totally dominated by the agent's idiosyncratic taste factors. Region-specific factors do not matter. This is the case in a fully integrated, dense labor market. The agent's decision on where to live is independent of the location of the job, and each living area h is chosen with probability x_h. The parameter γ_w can therefore be interpreted as a density index for region w. In other words, γ_w captures the importance of regional factors relative to idiosyncratic taste factors of the agents.

[1] Equation (2) is slightly more general than the condition $E(p_{wh}) = x_h$ applied by EG. The latter condition implies that x_h is nonstochastic. This seems to be inconsistent with their model, since x_h depends on the realizations of ε_{kwh} and must therefore be stochastic. However, this difference in presentation has no implications for Proposition 1 below.

Now we will define an unbiased estimator for γ_w. Let s_{wh} be the number of workers working in area w and living in area h as a share of total employment in area w. Then:

Proposition 1. Consider the case where K workers, distributed across work locations w with share f_w, choose their home location according to equations (1), (2), and (3). A consistent estimator for γ_w is

$$\operatorname*{plim}_{K\to\infty} \frac{\sum_h (s_{wh} - x_h)^2}{1 - \sum_h x_h^2}. \tag{4}$$

Proof. We have

$$\begin{aligned}
&\operatorname*{plim}_{K\to\infty} \left(\sum_h (s_{wh} - x_h)^2 \middle| p_{wh} \right) \\
&= \operatorname*{plim}_{K\to\infty} \sum_h E[(s_{wh} - x_h)^2 | p_{wh}] \\
&= \operatorname*{plim}_{K\to\infty} \sum_h [\mathrm{var}(s_{wh} - x_h | p_{wh}) + E^2(s_{wh} - x_h | p_{wh})] \\
&= \sum_h (p_{wh} - \mu_h)^2.
\end{aligned}$$

The second step uses $\mathrm{var}(s_{wh} - x_h | p_{wh}) = E[(s_{wh} - x_h)^2 | p_{wh}] - E^2(s_{wh} - x_h | p_{wh})$. The third step uses $\operatorname{plim}_{K\to\infty} \mathrm{var}(s_{wh} - x_h | p_{wh}) = 0$, $E(s_{wh} | p_{wh}) = p_{wh}$, and $E(x_h) = \mu_h$. Dropping the conditioning on p_{wh} and substitution of (2) and (3) yields

$$\begin{aligned}
&\operatorname*{plim}_{K\to\infty} \left(\sum_h (s_{wh} - x_h)^2 \right) \\
&= E_{p_{wh}}\left[\sum_h (p_{wh} - \mu_h)^2 \right] = \sum_h \mathrm{var}(p_{wh}) \\
&= \sum_h \gamma_w \mu_h (1 - \mu_h) = \gamma_w (1 - \sum_h \mu_h^2),
\end{aligned}$$

where we use $E(p_{wh}) = \mu_h$ in the second equality and $\sum_h \mu_h = 1$ in the final equality. Rearranging terms and using $E(x_h) = \mu_h$ gives (4). ■

To illustrate how this index is related to the scale of the labor market, consider a job in area w. Let there be N residential areas, each populated by a single worker, let n be the number of workers who are willing to work in area w, and let all of them have equal probability of getting the job. Hence, n is a measure for the scale of the labor market. The probability for each of the workers of getting this job is $1/n$, and the probability for the rest of the population, $N - n$, is equal to zero. In other words, $p_{wh} = 1/n$ with probability n/N, and $p_{wh} = 0$ with probability $1 - n/N$. Since the variance of a Bernoulli trial with success rate: n/N is $(1 - n/N)n/N$, the variance of p_{wh} is $V = (1/n)^2[(1 - n/N)n/N] = (1/N)[1/n - 1/N]$. According to equation (3), this is equal to: $\gamma(1/N)(1 - (1/N))$. Solving for γ and taking $\lim N \rightarrow \infty$ gives $\gamma \simeq (1/n)$. Hence, in this simple binomial example where workers either do or do not belong to a market for a particular job and where all workers in a market have an equal probability for that job, γ is equal to the reciprocal of the scale of the labor market.

The above analysis takes as a starting point the work area of the worker and then determines the choice of the optimal living area. We could also have proceeded the other way around, by analyzing the choice of the optimal work area conditional on the living area. The actual conditioning on work area in our calculations is based on the notion that a large fraction of city centers consists of offices. Then, conditioning on living area would underestimate the density of the city centers. Most people living in Manhattan are likely to work in Manhattan, incorrectly suggesting that Manhattan is a low-density area. However, most people working in Manhattan live in other regions. Hence, by conditioning on work areas we avoid the problem of the mismeasurement of γ_w in city centers.

Under the assumptions made, this index is independent of its level of aggregation.[2] Whether one measures location at (for example) the state level or the county level should not affect the calculated value of γ_w for a state. However, this requires that the values of $\{\bar{\pi}_{wh}\}$ be drawn independently of the aggregation scheme of subregions into regions. Obviously, this assumption is violated in reality. In practice, any aggregation merges adjacent subregions into a new region. The values of $\{\bar{\pi}_{wh}\}$ for subregions within a region will typically be correlated. The example below makes this clear.

Consider four regions of equal size ($x_h = 1/4$), each consisting of four agents and four jobs. In the first case all regions form a fully integrated market; $s_{wh} = 1/4$ for all h, w, and $\gamma_w = 0$. In the second case, $s_{wh} = 1/2$ for all h, w, and $\gamma_w = 1/3$. This is typical for the situation where 1 and 2 as well as 3 and 4 are twin cities. In the third case there are four fully separated markets: $s_{wh} = 1$ for all h, w, and $\gamma_w = 1$:

(1) $\gamma_w = 0$

w	$h = 1$	2	3	4
1	1	1	1	1
2	1	1	1	1
3	1	1	1	1
4	1	1	1	1

(2) $\gamma_w = 1/3$

w	$h = 1$	2	3	4
1	2	2	0	0
2	2	2	0	0
3	0	0	2	2
4	0	0	2	2

(3) $\gamma_w = 1$

w	$h = 1$	2	3	4
$w1$	4	0	0	0
$w2$	0	4	0	0
$w3$	0	0	4	0
$w4$	0	0	0	4

When we combine regions 1 and 2 and regions 3 and 4 into two new regions, we get

(1) $\hat{\gamma}_w = 0$

w	$h = 1, 2$	$h3, 4$
1, 2	4	4
3, 4	4	4

(2) $\hat{\gamma}_w = 1$

w	$h = 1, 2$	3, 4
1, 2	8	0
3, 4	0	8

(3) $\hat{\gamma}_w = 1$

w	$h = 1, 2$	3, 4
1, 2	8	0
3, 4	0	8

When $\gamma_w = 1/3$, combining regions 1 and 2 increases γ_w.[3] The extreme cases are invariant to the aggregation of regions. For the other cases, aggregation tends to overestimate γ_w. In the next section, we present estimates of γ_w for the United States and test whether aggregation affects the results.

III. Data

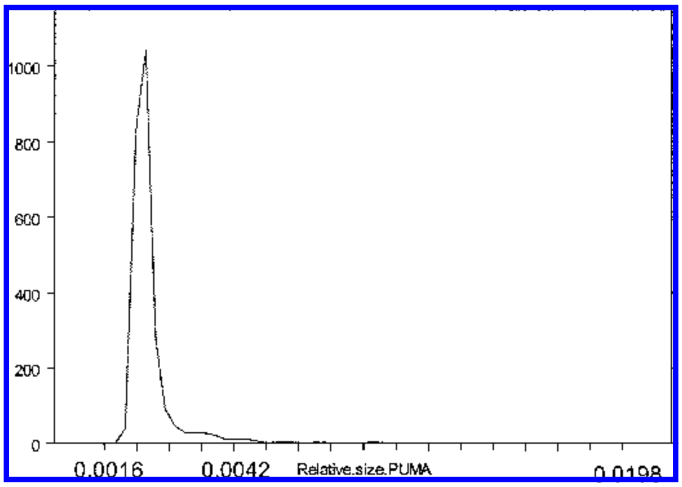
A. *Constructing the Index from Census Data*

The U.S. Census data are well suited for the construction of our index, because they contain detailed information on both the area of residence and the work area at low levels of aggregation. We use the 5% public-use micro samples (PUMS) of the 1990 Census. The most disaggregate geographic unit in the Census is the *public-use micro data area* (PUMA). A typical PUMA is populated by at least 100,000 persons and is identified by a five-digit number, which is

[2] There are two ways to think about aggregation in this context: (1) reducing the number of areas for which we calculate γ_w and (2) taking weighted averages of γ_w over neighboring areas. The discussion in this section is about (1); in section IV we consider (2).

[3] Note that if we had used the combined regions 1,4 and 2,3 or 1,3 and 2,4, this would have reduced γ_w, but in practice this is not relevant, because aggregation schemes tend to combine adjacent and integrated subregions.

FIGURE 1.—DENSITY OF AREA SIZES: MEAN = 0.001, σ^2 = 0.001



unique within states. In dense areas, PUMAs are a subset of a single county, whereas in rural states, PUMAs typically consist of several different counties. To construct our density index we also need information on the area where the worker works (PUMAW). This is however defined at the two-digit level (unique by state), which will be the level of our analysis. With the method of the previous section we were able to construct a γ_w for each of the 1138 two-digit PUMAs.

In calculating γ_w, we only included the full-time employed workers and excluded Alaska and Hawaii. Since in general, each area is very small compared to the whole country, the denominator of (4) is close to 1 (namely, using Census data, we found for the U.S. $\Sigma_w x_h^2 = 0.0024$), and γ_w is therefore almost entirely determined by $\Sigma_h(s_{wh} - x_h)^2$. To get an idea of the range of possible values γ_w can attain, we found γ_w to be equal to 0.07 in northern New Jersey, whereas for some areas in Arizona, Maine, Missouri, Montana, Kansas, and Wyoming we found values of γ_w as high as 0.95. The distribution of PUMA's population shares is plotted in figure 1. Both the mean and the standard deviation of these population shares are 0.001. It suggests that we do not have to worry about aggregation bias. This is confirmed by a simple OLS regression of log γ_w on the log population shares of the area, which shows that there exists an insignificant positive relation between γ_w and area size (the elasticity is 0.02, $t = 0.56$).

B. *Using Additional Information from the CPS*

For many economic applications, the CPS contains crucial individual information which is not present in the Census. That is why we aggregated up our index to the (C)MSA × state level. This is not a trivial operation, because there is no one-to-one match between the PUMAs of the Census and the (C)MSA (central metropolitan area) and state classification of the CPS. We therefore use the following strategy. First, we match the PUMAWs to (C)MSAs, using the method of Jaeger et al. (1998). We aggregate by taking weighted (by population share) averages of the relevant γ_w's. In most states there are however areas which do not belong to a (C)MSA. Those are typically rural areas. For those areas we also calculated weighted average γ_w's per state.[4] Finally, there are some small (C)MSAs that consist of only one PUMA. When those areas are isolated (for example, Tucson, Phoenix) or close to the Mexican border (El Paso), this overestimates γ_w for the reasons we discussed in section II. We therefore treat (C)MSAs consisting of only one PUMA like the within-state areas that do not belong to a (C)MSA. This leaves us with in total 164 γ_w's.

To illustrate the aggregation procedure, consider the following example for Indianapolis, IN. The Indianapolis CMSA consists of four PUMAs, each with a unique γ_{Census}. In the CPS, Indianapolis is treated as a single geographical unit. We take weighted (by x_w) averages of γ_{Census} to get a unique γ_{CPS} for Indianapolis.

Figure 2 plots density distributions for both the 1138 Census PUMAs and the 164 CPS areas. The mean for γ_{Census} is 0.597, and the standard deviation is 0.235; for γ_{CPS} those values are respectively 0.574 and 0.185. From this, we conclude that we do not lose much variation in our index by aggregating up to the (C)MSA × state level, suggesting that the CPS regions are quite homogeneous with respect to their γ. The overall shapes of the distributions are quite similar, they are bimodal with one hump at $\gamma = 0.80$; the other hump is at $\gamma = 0.25$ for the Census and at $\gamma = 0.40$ for the CPS.[5]

We expect γ_w to be related to population density (measured in persons per square mile). Figure 3 is illustrative in this respect. Figure 3 shows a map of all the counties in the United States, where the darker areas are more densely populated. In this figure we have inserted some values of γ_w, based on the Census PUMAs. We clearly see that densely populated areas have smaller γ_w's. The correlation between γ_{CPS} and people per square mile is -0.43.

IV. Application: Estimation of a Wage Equation

In this section we look at the effect of our labor market density index on wages. This application merely serves as an illustration. We do not have a narrow structural interpretation of our estimation results. In the literature, several reasons for the existence of cross-regional wage differentiation have been put forward: regional differences in the efficiency of the matching process, as in Teulings and Gautier (2002) and Wheeler (2002); knowledge spillovers,

[4] For the definitions of (C)M(S)As we refer to Appendix A. Our density measures and relevant weights per PUMAW of the 1990 census and per (C)MSA/MA of the CPS, as well as SAS formats for (C)MSAs and states, can be found at http://www.tinbergen.nl/~gautier/lmdensity.html.

[5] See Appendix B for a full listing of γ.

FIGURE 2.

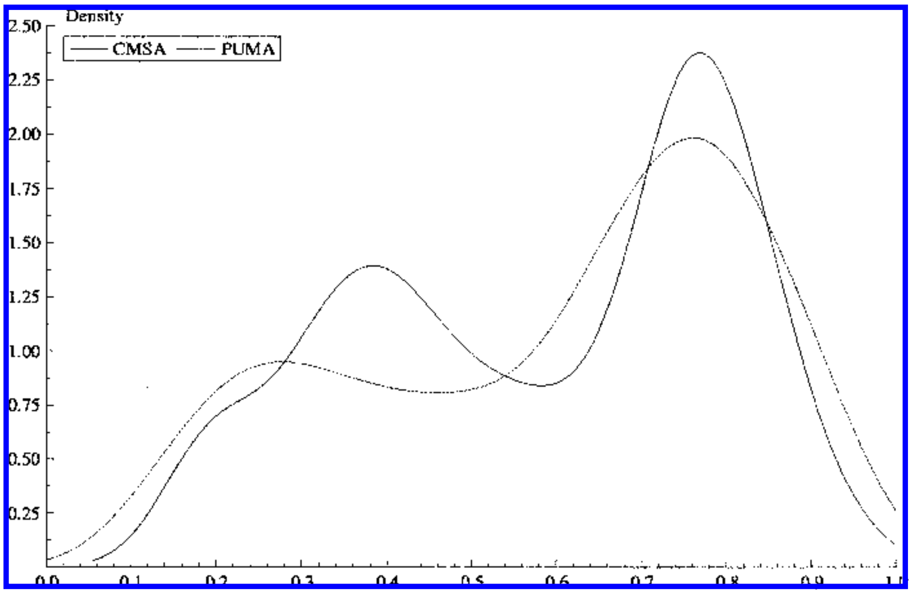


FIGURE 3.—THE RELATION BETWEEN PERSONS PER SQUARE MILE AND Γ_{CPS}

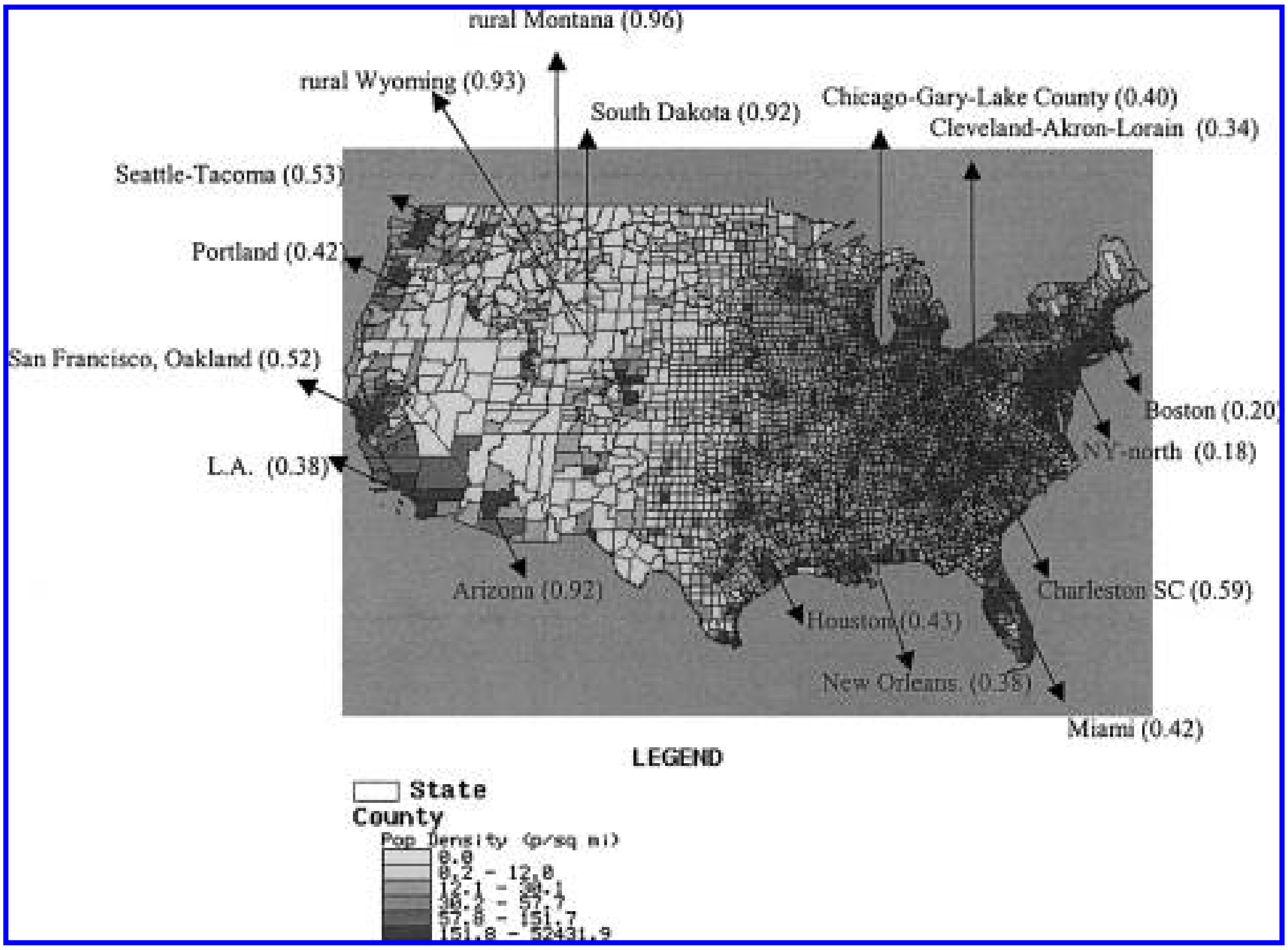


TABLE 1.—ESTIMATION RESULTS

Est.	Ind. Var.	N	R^2	Estimate	t-Value
		Dependent Variable: Log Hourly Wage			
1	γ	150	0.454	−0.391	11.10
2	γ	150	0.484	−0.403	11.43
	avsize			6.109	1.41
3	γ	150	0.553	−0.382	11.31
	ncmw			−0.061	3.36
	south			−0.085	5.05
	west			−0.028	1.30
4	γ	95	0.242	−0.294	5.46
5	γ	95	0.415	−0.185	3.64
	ppsqm			0.096	4.12
6	γ	95	0.4388	−0.175	3.25
	ppsqm			0.083	3.56
	ncmw			−0.025	0.24
	south			−0.056	2.90
	west			0.004	0.90
		Dependent Variable: Log Cost of Living			
7	γ	95	0.212	−0.348	5.24
8	γ	95	0.531	−0.118	1.99
	ppsqm			0.024	8.03
9	γ	95	0.676	−0.087	1.74
	ppsqm			0.018	8.27
	ncmw			−0.082	4.19
	south			−0.089	4.93
	west			0.005	0.20
		Dependent Variable: Log Hourly Wage (Census)			
10	γ	1097	0.204	−0.066	16.76

as in Lucas (1988) and Glaeser and Maré (2001); or compensating differentials, as in Roback (1982). For our purposes it is enough that wages are correlated with labor market density. We are interested in the fraction of the cross-regional variance in wages that can be attributed to our labor market density index. If density matters, it should pick up a substantial part of the cross-regional variation in wages. We use both the March 1991 supplements of the CPS and the 1% PUMS of the 1990 Census for our wage equation. Most of our attention goes to the CPS results, because that allows for a more accurate calculation of earnings and hours worked. In the PUMS, working time was measured as an interval variable, which makes the hourly wage rate less accurate.[6]

Directly estimating the effect of γ on log wages with OLS gives an unbiased estimate of λ, but it produces downwardly biased standard errors in the presence of within-region correlation of the disturbances; see Moulton (1990). Therefore, the following equations are estimated by OLS:

$$\log w_{ij} = \beta_0 + \beta_2 X + \beta_j R_j + \varepsilon_{ij}, \quad (5)$$

$$\beta_j = \lambda_0 + \lambda_1 \gamma + v_j, \quad (6)$$

where log w_{ij} is the log (gross) hourly wage of worker i from region j, and X_1 contains all the standard variables of the wage equation;[7] R_j is a set of region dummies. Equation (5) was estimated once on all regions and once on the 95 (C)MSAs for which we have additional information on people per square mile and cost of living. We experimented in equation (6) with various extra controls. The results are presented in table 1.

We can conclude from estimation 1 that our density index explains 45% of the cross-regional wage variation that is not

[6] An additional problem of measuring the effect of labor market density on wages at the PUMA level is, as the referees pointed out, that the causality might be reversed. Firms in highly productive regions could post higher wages to attract workers from other regions. In the CPS estimates, this mechanism is not relevant, because there we use regions that consist of multiple PUMAs, so that in general both home and work location are in the same region. The mechanism described above would then generate within-region wage differentials, whereas our estimates are based upon between-region wage differentials.

[7] The explanatory variables are: a constant, female, unmarried, female × unmarried, black, two-digit occupation and industry dummies, dummies for completed education (12, 14, 16, 18 years), education (years), and cubic polynomials in experience, experience × education, female × experience, female × (not married), and female × (not married) × experience. Here $N = 66{,}211$.

explained by the standard observable worker characteristics. The estimated value of λ_1 is highly statistically significant: Workers living in an area with a γ that is 1 standard deviation (0.19) left from the mean earn 7.4% more than people living in an area where γ is equal to its mean. In estimation 2 we include average PUMA size as an explanatory variable to test whether the potential aggregation bias that we discussed in section II plays a role. It does not. Its effect is not significant, and λ remains almost the same. Next, we add dummies for the main regions: North Central/Midwest, South, and West (Northeast is control). Wages in the Northeast turn out to be higher. Our density index only decreases slightly. In estimation 5, we test whether controlling for people per square mile eliminates the effect of our density index. This turns out not to be the case. λ_1 drops but remains significant. Because we only have people-per-square-mile (ppsqm) data at the (C)MSA level, we also repeated estimation 1 with the same regions as in estimation 5 to check to what extent the fall in λ is due to fewer observations or to including ppsqm; the result is estimation 4. It turns out that the inclusion of ppsqm makes λ_1 fall from -0.29 to -0.19. The drop in λ due to leaving the non-(C)MSA areas out is similar in magnitude: from -0.39 to -0.29. In estimation 6 we included region dummies, and λ_1 remains stable at -0.17 (3.11).

If, for the reasons we mentioned above, dense areas are attractive and if the stock of real estate is to some extent fixed, then the real estate owners receive rents. We therefore expect our index to be correlated with the cost of living. To see to what extent this is the case, we add the regional cost-of-living index of Dumond, Hirsch, and MacPherson (1999). This index is based on the American Chamber of Commerce Researchers Association (ACCRA) cost-of-living index for the period 1985:4 through 1995:2. In estimations 7, 8, and 9 we see that this measure is also positively related to both our density index and people per square mile.

In estimation 10, we estimate the effect of our density index at the PUMA level of aggregation with data from the 1% PUMS of the Census; see Ruggles and Sobek (1997).[8] The estimate of λ in the equivalent of estimation 6 is -0.066 (16.76). Again, we conclude that workers in denser areas earn higher wages.[9]

V. Discussion

We have shown that we can give a meaningful structural labor market interpretation of the Ellison and Glaeser (1997) index of concentration. The large and significant effect that our density index has on wages suggests that it captures important effects. Our index is particularly useful for testing theories that predict that the scale of the labor market matters. From a theoretical point of view, our index is more attractive than the obvious alternative: people per square mile. This index is available for (C)MSA's only. For those regions for which it is available, our index and people per square mile are correlated. However, both are statistically significant in a wage equation. In Teulings and Gautier (2002), we successfully apply our density index to analyze the effect of the efficiency of the search process on the distribution of workers and jobs across regions.

[8] We have 224,271 observations.

[9] When we aggregate up the Census regions to the CPS levels and place the same restrictions on the hours-worked variable in the CPS, the Census estimate of the density index remains considerably smaller than the CPS one. The correlation between the sets of regional dummies obtained from estimation 5, using the Census data and the CPS data, is only 0.31.

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APPENDIX A

Definitions

- *MSA:* Relatively freestanding and not closely associated with other MAs. Typically surrounded by nonmetropolitan areas. The title of an MSA contains the name of its largest city and up to two additional city names.
- *CMSA:* Consolidated metropolitan area. MA of more than 1 million people, which may include one or more large urbanized counties that display very strong internal economic and social links within a CMSA. An example of a large CMSA is New York–New Jersey–Long Island.

APPENDIX B

TABLE B1.—STATES AND ASSOCIATED (C)MSAS RANKED FROM DENSE TO NONDENSE

Rank	State	(C)MSA	γ	Rank	State	(C)MSA	γ
1	DC	Washington	0.18201	83	Ohio	Youngstown–Warren	0.58012
2	New Jersey	NY–North. NJ–Long Island	0.18420	84	Nevada	Reno	0.58201
3	Florida	Orlando	0.19529	85	Ohio	Dayton–Springfield	0.58718
4	Massachusetts	Boston–Lawernce–Salem–Lowell–Brockton	0.19993	86	Nebraska	Omaha	0.59182
5	Minnesota	Minneapolis–St. Cloud	0.21236	87	Wisconsin	Milwaukee–Racine	0.59276
6	Connecticut	Hartford–New Britain–Middletown–Bristol	0.26075	88	South Carolina	Charleston	0.59322
7	Connecticut	NY–North. NJ–Long Island	0.26413	89	North Carolina	Raleigh–Durham	0.59538
8	New Jersey	Philadelphia–Wilmington–Trenton	0.28888	90	Colorado	Colorado Springs	0.59608
9	Texas	Dallas–Fort Worth	0.30358	91	Texas	San Antonio	0.59681
10	Colorado	Denver–Boulder	0.30739	92	Wisconsin	Appleton–Oshkosh–Neenah	0.60155
11	Massachusetts	Worcester	0.31041	93	North Carolina	Charlotte–Gastonia–Rock Hill	0.60192
12	Connecticut	New Haven–Meriden	0.31172	94	New Hampshire	Non-(C)MSA area	0.60363
13	Michigan	Detroit–Ann Arbor	0.31810	95	California	Salinas–Seaside–Monterey	0.61512
14	Rhode Island	Providence–Pawtucket–Woonsocket	0.31855	96	Ohio	Toledo	0.61773
15	Georgia	Atlanta	0.32859	97	Indiana	Louisville	0.61824
16	New Jersey	Atlantic City	0.33552	98	Florida	Fort Pierce	0.62039
17	New York	Buffalo–Niagara Falls	0.33560	99	Alabama	Birmingham	0.62628
18	Ohio	Cleveland–Akron–Lorain	0.34439	100	Alabama	Montgomery	0.62861
19	Virginia	Richmond–Petersburg	0.34729	101	Tennessee	Johnson City–Kingsport–Bristol	0.62942
20	New York	NY–North. NJ–Long Island	0.34776	102	South Carolina	Non-(C)MSA area	0.64862
21	Michigan	Lansing–East Lansing	0.35209	103	Michigan	Saginaw–Bay City–Midland	0.64866
22	Virginia	Washington	0.36757	104	Ohio	Columbus	0.66128
23	Louisiana	Baton Rouge	0.37122	105	South Carolina	Greenville–Spartanburg	0.66141
24	Tennessee	Chattanooga	0.37835	106	Pennsylvania	Pittsburgh–Beaver Valley	0.67295
25	New York	Albany–Schenectady–Troy	0.37913	107	Georgia	Non-(C)MSA area	0.67496
26	California	Los Angeles (city)	0.37934	108	Ohio	Non-(C)MSA area	0.67521
27	Louisiana	New Orleans	0.38304	109	Oklahoma	Tulsa	0.67564
28	Massachusetts	Springfield	0.38791	110	Indiana	Non-(C)MSA area	0.68770
29	New York	Syracuse	0.38889	111	Delaware	Non-(C)MSA area	0.69159
30	Massachusetts	Providence–Pawtucket–Woonsocket	0.39096	112	Maryland	Non-(C)MSA area	0.69311
31	Kentucky	Louisville	0.39682	113	New York	Binghamton	0.69981
32	Indiana	Chicago–Gary–Lake County	0.39885	114	Utah	Salt Lake City–Ogden	0.71502
33	Maryland	Baltimore	0.40908	115	Vermont	Non-(C)MSA area	0.71874
34	Michigan	Grand Rapids	0.41137	116	Florida	Jacksonville	0.71967
35	Tennessee	Knoxville	0.41209	117	Indiana	Evansville	0.72104
36	Illinois	St. Louis	0.41564	118	Pennsylvania	York	0.72320
37	Florida	Miami–Fort Lauderdale	0.41688	119	Pennsylvania	Scranton–Wilkes-Barre	0.72731
38	Oregon	Portland	0.41916	120	Mississippi	Non-(C)MSA area	0.72741
39	Illinois	Chicago–Gary–Lake County	0.41966	121	Virginia	Non-(C)MSA area	0.72983
40	Kentucky	Cincinnati–Hamilton	0.42248	122	West Virginia	Non-(C)MSA area	0.73126
41	Missouri	St. Louis	0.42903	123	Alabama	Non-(C)MSA area	0.73288
42	Maryland	Washington	0.43077	124	Georgia	Augusta	0.73401
43	Texas	Houston–Galveston–Brazoria	0.43306	125	Iowa	Non-(C)MSA area	0.73448
44	Connecticut	Non-(C)MSA area	0.43436	126	New York	Utica–Rome	0.73627
45	Virginia	Norfolk–Virginia Beach–Newport News	0.43863	127	North Carolina	Non-(C)MSA area	0.74169
46	Michigan	Flint	0.44093	128	Maine	Non-(C)MSA area	0.74180
47	Illinois	Rockford	0.44260	129	Arkansas	Little Rock–North Little Rock	0.74541
48	North Carolina	Fayetteville	0.44308	130	Kentucky	Non-(C)MSA area	0.74660
49	Connecticut	New London–Norwich	0.44369	131	Virginia	Johnson City–Kingsport–Bristol	0.74663
50	Pennsylvania	Philadelphia–Wilmington–Trenton	0.44455	132	Tennessee	Non-(C)MSA area	0.75257
51	Kansas	Kansas City	0.44475	133	Michigan	Non-(C)MSA area	0.75505
52	North Carolina	Greensboro–Winston–Salem–High Point	0.45378	134	New York	Non-(C)MSA area	0.75518
53	California	Sacramento	0.47082	135	Illinois	Non-(C)MSA area	0.75701
54	California	Modesto	0.47128	136	Florida	Tampa–St. Petersburg–Clearwater	0.76119
55	Tennessee	Memphis	0.48094	137	Texas	Killeen–Temple	0.76615
56	Texas	Beaumont–Port Arthur	0.48404	138	Wisconsin	Non-(C)MSA area	0.76934
57	Ohio	Cincinnati–Hamilton	0.48589	139	Texas	Corpus Christi	0.76942
58	Florida	Melbourne–Titusville–Palm Bay	0.49493	140	Arkansas	Non-(C)MSA area	0.77266
59	Washington	Spokane	0.49705	141	Washington	Non-(C)MSA area	0.77861
60	Pennsylvania	Harrisburg–Lebanon–Carlisle	0.49721	142	Missouri	Non-(C)MSA area	0.79070
61	Missouri	Kansas City	0.49750	143	Minnesota	Non-(C)MSA area	0.79186
62	Indiana	Fort Wayne	0.49753	144	Pennsylvania	Non-(C)MSA area	0.79400
63	South Carolina	Columbia	0.50242	145	Alabama	Mobile	0.80454
64	California	Fresno	0.50661	146	Louisiana	Non-(C)MSA area	0.80639
65	New York	Rochester	0.50816	147	Kansas	Wichita	0.80993
66	Texas	Austin	0.51424	148	New Mexico	Non-(C)MSA area	0.82036
67	Iowa	Des Moines	0.51545	149	Florida	Non-(C)MSA area	0.82273
68	California	San Francisco–Oakland–San Jose	0.51671	150	North Dakota	Non-(C)MSA area	0.82542
69	California	Bakersfield	0.52003	151	Colorado	Non-(C)MSA area	0.85206
70	Washington	Seattle–Tacoma	0.53220	152	California	Non-(C)MSA area	0.86129
71	Mississippi	Jackson	0.53408	153	Nebraska	Non-(C)MSA area	0.86141
72	Indiana	Indianapolis	0.53501	154	Idaho	Non-(C)MSA area	0.86383
73	Wisconsin	Madison	0.53776	155	Kansas	Non-(C)MSA area	0.86384
74	Tennessee	Nashville	0.54252	156	Oklahoma	Non-(C)MSA area	0.87242
75	Oregon	Eugene–Springfield	0.54305	157	Oregon	Non-(C)MSA area	0.87992
76	Illinois	Peoria	0.54461	158	Utah	Non-(C)MSA area	0.89160
77	Pennsylvania	Allentown–Bethlehem	0.55004	159	Texas	Non-(C)MSA area	0.89445
78	Massachusetts	Non-(C)MSA area	0.55970	160	Arizona	Non-(C)MSA area	0.91724
79	Kentucky	Lexington–Fayette	0.56318	161	South Dakota	Non-(C)MSA area	0.91771
80	Illinois	Davenport–Rock Island–Moline	0.56678	162	Nevada	Non-(C)MSA area	0.92344
81	Oklahoma	Oklahoma City	0.57660	163	Wyoming	Non-(C)MSA area	0.93019
82	Georgia	Macon–Warner Robins	0.57871	164	Montana	Non-(C)MSA area	0.94790